Modelling and Analysis of Communication Traffic Heterogeneity in Opportunistic Networks

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Abstract—In opportunistic networks, direct communication between mobile devices is used to extend the set of services accessible through cellular or WiFi networks. Mobility patterns and their impact in such networks have been extensively studied. In contrast, this has not been the case with communication traffic patterns, where homogeneous traffic between all nodes is usually assumed. This assumption is generally not true, as node mobility and social characteristics can significantly affect the end-to-end traffic demand between them. To this end, in this paper we explore the joint effect of traffic patterns and node mobility on the performance of popular forwarding mechanisms, both analytically and through simulations. Among the different insights stemming from our analysis, we identify conditions under which heterogeneity renders the added value of using extra relays more/less useful. Furthermore, we confirm the intuition that an increasing amount of heterogeneity closes the performance gap between different forwarding policies, making end-to-end routing more challenging in some cases, or less necessary in others. To our best knowledge, this is the first effort to model, analyze, and quantify effects of traffic heterogeneity. We believe this is an important step towards better protocol design and evaluation of the feasibility of applications in opportunistic networks.

Index Terms—opportunistic networks, delay tolerant networks, performance analysis, heterogeneous mobility, heterogeneous traffic

1 INTRODUCTION

OPPORTUNISTIC or Delay Tolerant Networks (DTNs) [1] were initially envisioned to support communication in challenging environments, where infrastructure is limited or absent (e.g. emergency situations after disasters, mobile sensor networks). Lately, it has been suggested that they could also support or enhance existing networking infrastructure, e.g. by offloading traffic from cellular networks, enabling novel social and location-based applications, or introducing peer-to-peer collaborative computing [2], [3].

Opportunistic networks consist of mobile nodes (e.g. smartphones, laptops) that exchange data directly when they are *in contact* (i.e. within transmission range). Due to the limited range of direct communication (e.g. Bluetooth), communication is not continuous, and maintaining end-to-end paths is problematic. If nodes are not willing to relay 3rd party traffic, a message can only be transferred from a source node to a destination node when they come in contact (*direct transmission routing* [4]). If other nodes are willing to collaborate, they could copy the message from the source (or another relay), *store* and *carry* it and, finally, *forward* it when they encounter the destination node. Such replication and relaying schemes could improve performance (*relay-assisted routing*, e.g. [5], [6], [7]), albeit at increased complexity and resource overhead.

Since message exchanges take place only during contacts between nodes, mobility plays a major role both in the performance and the design of protocols and applications. As a result, sophisticated utility-based schemes have been proposed that select relays based on their mobility patterns and/or social characteristics [8]. Furthermore, a lot of effort has been made recently to capture the mobility patterns of real networks [9], [10], [11], [12]. These mobility patterns can often greatly affect the performance of different schemes.

Somewhat surprisingly, the communication traffic patterns used in studies of opportunistic networks have not received an equal amount of attention. It is usually assumed, implicitly or explicitly, that all traffic is uniform: each pair of nodes exchanges the same amount of messages. However, intuition suggests that traffic between nodes, just like contacts, cannot be expected to be homogeneous either. This is also supported by empirical studies on social networks [13], [14], where the frequency of message exchanges might widely vary among pairs of nodes. Further, nodes that have a social relation or reside/move in the same areas, often tend to exchange more messages than others. Therefore, a number of interesting questions arise: *How should one model the heterogeneity in communication traffic? Do heterogeneous traffic patterns affect the performance of information dissemination mechanisms and to what extent?*

Towards answering this question, in this paper we investigate *if*, *when* and *how* traffic patterns affect the communication performance in opportunistic networks. Specifically:

- We examine what characteristics of traffic heterogeneity can have an effect on performance, and show that only when (end-to-end) traffic demand is correlated with pairwise contact rates performance is affected. Based on these findings, we propose an analytically tractable model that can describe a large range of non-uniform traffic patterns (Section 2).
- We derive analytical expressions for calculating the joint effect of traffic and mobility heterogeneity in the performance of basic forwarding mechanisms (Section 3).
- We use these expressions to show that the common understanding about these mechanisms, e.g. the gains from having additional replicas, might radically change when traffic is heterogeneous (Sections 3.2 and 3.3).

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• We validate our analytical findings through simulations (Section 4.1) and, by applying them to datasets of real-world networks that contain information about the mobility and communication patterns of participating nodes (Section 4.2).

• Finally, we present possible extensions of our study (Section 5), and discuss related work (Section 6) and further research directions on traffic patterns for opportunistic networking (Section 7).

To our best knowledge, this is the first attempt to model end-to-end traffic heterogeneity and analytically study its (quantitative and qualitative) effects on the performance of opportunistic communications. Our analytical findings, as well as simulation results, reveal important aspects of opportunistic networking that have not been explored or have not been taken into account in previous studies:

– When frequently meeting node pairs tend to exchange (on average) more/less traffic than other nodes, the communication performance can considerably differ from the homogeneous case. Taking into consideration such traffic patterns allows to better design or tune routing protocols.

– The effects on some forwarding mechanisms, like Direct Transmission [4], can be significant, while at the same time flooding (e.g. Epidemic [15]) or routing (e.g. Spray and Wait [5], EBR [16]) protocols are less affected. In particular, an increasing amount of heterogeneity closes the performance gap between the best (Epidemic) and the worst (Direct Transmission) forwarding.

– Under certain conditions, the impact of traffic heterogeneity can be so important, that it can lead to a reconsideration of the employed communication mechanisms, and even the feasibility of applications (e.g. online social messaging, file sharing, service composition) over opportunistic networking.

2 Network Model

2.1 Mobility

We consider a network $\mathcal{N}$, where N nodes move in an area, much larger than their transmission range. Data packet exchanges between a pair of nodes can take place only when they are in proximity (*in contact*). Hence, the dissemination of a message is subject to nodes mobility and the resulting *contact events*. To model this sequence of contact events, we will assume the following *class* of heterogeneous contact models.

Definition 1 (Heterogeneous Contact Network)**.**
Assumption 1. *Contact events between a pair of nodes $\{i, j\}$ follow a Poisson process with rate λ_{ij}, i.e. inter-contact times are independent and exponentially distributed with rate λ_{ij}.*
Assumption 2. *Contact rates λ_{ij} are independently drawn from an arbitrary distribution with probability density function $f_\lambda(x)$ (with finite mean μ_λ and variance σ^2_λ).*
Assumption 3. *Contact duration is negligible compared to the time between contacts events, though sufficient for all data transfers to take place.*

The assumption of Poisson contacts is common in the majority of previous studies in Opportunistic / Delay Tolerant Networks [9], [11], [12], [17], [18], and allows one to use a Markovian framework for analyzing dissemination processes. In addition, analyses of real-world contact traces provide some support, suggesting that the observed inter-contact time distributions (or, at least, their *tails*) can often be approximated by exponential distributions [19], [20]. While this assumption can sometimes be relaxed, to our best knowledge this only applies to asymptotic analysis [21], [22].

The second assumption introduces some heterogeneity in the standard model [5], [18], [23], which normally assumes homogeneous contact rates (i.e. $\lambda_{ij} = \lambda$ for all pairs)[1], in an attempt to better align the model with the findings of real-world trace analyses showing that the contact rates (or frequencies) of different pairs are largely heterogeneous [10], [17], [19]. Moreover, by allowing rates to be drawn from an arbitrary distribution f_λ, we can (i) emulate a very diverse set of contact (and thus mobility) scenarios, and (ii) fit this distribution to match the rates observed in a real trace.

The third assumption is equivalent to saying that there are no bandwidth concerns in our framework. Although this is not always true [8], it is orthogonal to the main topic of our study.

Summarizing, our main motivation for this model is to maintain the analytical tractability properties of standard models, while also integrating some mobility heterogeneity, whose joint effect with traffic heterogeneity we want to investigate. To ensure that our assumptions do not confound the conclusions drawn from our analysis, we will validate our results against real measurement traces, where many of these assumptions are known to not hold.

2.2 Communication Traffic

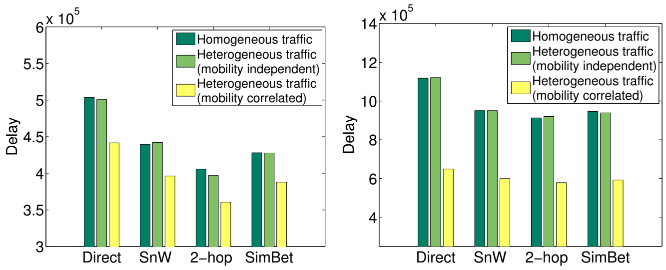
In addition to who contacts whom and how often, another major question that should be raised in opportunistic networks (but rarely is) is *who wants to communicate with whom* and *how much traffic do they exchange*?

Intuition suggests that every pair of nodes will not exchange the same amount of traffic. To support intuition, studies from fields related to technological and social networks [13], [14], [25] have demonstrated the existence of heterogeneous traffic patterns. The same studies further suggest that this heterogeneity depends on the *spatial* and *social* characteristics of these networks. Since *location-based services* [26] and *social networking* [27] are considered among the major applications supported by opportunistic networks, such traffic dependencies on social and/or spatial factors are very probable to appear. What is more, mobility characteristics have also been found to depend on spatial and social characteristics [10], [28], [29]. This clearly seems to argue for a non-homogeneous traffic model. Moreover, traffic and mobility in such networks are expected to exhibit some correlations [13], [14].

Before we proceed to choose a traffic model, one should consider the following questions: *Would the mere heterogeneity of traffic suffice to affect performance? Is it necessary to consider traffic and mobility correlations?*

As stated earlier, information dissemination is determined by the sequence of contact events. Hence, if traffic character-

1. Some notable exceptions include [9], [11], [12], [17], [24].



(a) Gowalla dataset (b) Strathclyde dataset

Fig. 1. Mean delivery delay of 4 routing protocols, namely *Direct Transmission*, *Spray and Wait* (*SnW*), *2-hop*, and *SimBet*, on the (a) Gowalla and (b) Strathclyde datasets.

istics are independent of node mobility, one might expect a limited impact on performance.

Towards examining the validity of the above argument, we decided to compare the performance of some well-known opportunistic protocols (direct transmission [4], spray and wait [5], 2-hop routing [18], and SimBet [7]) through simulations on two real traces (we discuss the traces in more detail, later, in Section 4), for three traffic scenarios: (i) homogeneous traffic: every pair of nodes has the same chance of being chosen as the source-destination pair for the next message; (ii) heterogeneous traffic that is *mobility independent*: we assign randomly to each pair a different end-to-end traffic demand (with the normalized message generation rate for a pair drawn uniformly in $[1, 1000]$); (iii) heterogeneous traffic that is *mobility dependent*: end-to-end traffic between two nodes is proportional to their contact rate. We generated an equal (sufficiently large) number of messages for all scenarios.

Results for the mean message delivery delay are shown in Fig. 1. As is evident from these results, when traffic heterogeneity is independent of mobility (middle bar), the average delay is practically the same to the homogeneous case (left bar), *for all protocols, and across all scenarios* (including additional ones we have tried). In contrast, when traffic is heterogeneous *and* correlated with the contact rates (rightmost bar), Fig. 1 shows a clear difference in average delay for all scenarios and protocols. These results provide an initial answer to the above questions:

It is not traffic heterogeneity itself that affects performance, but rather the joint effect of mobility and traffic (heterogeneity).

In other words, unless differences in traffic demand correspond also to differences in contact frequency (e.g. frequently meeting pairs tend to also consistently generate more/less traffic for each other), end-to-end performance will not be affected. This statement is also formally proven in in Lemma 1 (Section 8.4).

The above observation, together with the initial insight coming from real datasets, motivates us to propose the following simple, yet quite generic, model for end-to-end traffic.

Definition 2 (Heterogeneous Communication Traffic)**.** *The end-to-end traffic demand (per time unit) between a pair of nodes $\{i, j\}$, is a random variable τ_{ij}, such that $E[\tau_{ij}] = \tau(\lambda_{ij})$, where $\tau(\cdot)$ is a continuous function from $\mathbb{R}^+$ to $\mathbb{R}^+$.*

Hence, traffic demand between node pairs can differ and is *on average* correlated with the nodes' contact rate. However, τ_{ij} itself is still random, allowing some node pairs to have little traffic demand even if they meet often (e.g. "familiar strangers"). Furthermore, through the function $\tau(\cdot)$ one can introduce a number of different types and amounts of (positive or negative) correlations between traffic and mobility. While real mobility and traffic patterns are clearly expected to have a number of additional nuances and details, not captured by the models of Def. 1 and Def. 2, it turns out that these abstractions are still "rich" enough to allow us to draw useful conclusions.

3 Analysis

Consider now an opportunistic network with mobility and traffic according to the definitions of Section 2. To calculate a performance metric for this network, e.g. the expected delay, one would consider a large number of messages generated between various source-destination pairs. Therefore, one would further need to know the contact rates between the sources and destinations of these messages. If a message was equally likely to be generated between any pairs of nodes, then the contact rate between the source and destination of this message should be distributed as f_λ (Def. 1). However, if messages are more like to come from a frequently meeting pair rather than an "average" pair, then the source-destination contact rate (we refer to it as the *effective* contact rate) would be biased towards higher values.

To this end, we derive the following basic proposition (whose proof is given in Section 8.1) for the probability distribution of the *effective* contact rates between source destination node pairs.

Proposition 1. *The probability density function f_τ of the contact rate between the source and the destination $\{s, d\}$ of a random message, in a network following Definitions 1 and 2, converges as follows:*

$$f_\tau(x) \xrightarrow{p} \frac{1}{\mathcal{C}} \cdot \tau(x) \cdot f_\lambda(x) \tag{1}$$

where $f_\tau(x)dx = P\{\lambda_{sd} \in [x, x + dx)\}$, $\xrightarrow{p}$ denotes convergence in probability, and $\mathcal{C} = E[\tau(\lambda)] = \int_0^\infty \tau(x)f_\lambda(x)dx$ is a normalizing constant.

As Proposition 1 shows, the source-destination contact rate distribution depends both on the contact rate distribution $f_\lambda(\lambda)$ and the traffic patterns $\tau(\lambda)$ (i.e. *joint effect of mobility and traffic*). Specifically, the probability that the contact rate of a selected node pair takes a certain value, e.g. $\lambda_{sd} \in [x, x+dx)$, is proportional to the number of pairs that contact with rate $\lambda_{ij} \in [x, x+dx)$ (i.e. $\propto f_\lambda(x)$) and the average traffic demand between them (i.e. $\propto \tau(x)$).

3.1 End-to-end Delivery Performance

An opportunistic routing protocol tries to deliver the end-to-end traffic demand τ_{ij}, and we would like to consider the effects of different contact patterns f_λ and traffic patterns $\tau(\lambda)$ on its performance. There exists a very large abundance of proposed schemes [8] and it would not be possible, nor would it provide any intuition, to analyze the effect of heterogeneity on each and every one. Instead, we focus here on some basic mechanisms to gain intuition.

The approach with the minimum overhead and complexity is *Direct Transmission ("DT")*: nodes wishing to exchange data or information with each other, may do so, only when they are in direct contact, without involving any relays. For instance, *DT* is often assumed in content-centric applications, where a node interested in some content will query directly encountered nodes for content of interest, and retrieve it only if it is available there. Furthermore, it is the only feasible approach if nodes do not have incentives to relay traffic they are not personally interested in, e.g. due to privacy or resource-related concerns [30]. Nevertheless, *DT* is known to suffer from long delays and low throughput [31].

To improve the performance of direct transmission, *replication* or *relay-assisted* schemes can be used. Extra copies can be handed over to encountered nodes, and the destination can receive the message from either the source or any of the relays, reducing thus the expected delivery delay. Taken to the extreme, schemes like epidemic routing [15] forward the message at every possible encounter (deterministically, probabilistically, or based on some utility-function). Yet these do not usually scale well beyond networks with few tens of nodes, due to large resource usage. Instead, few relays are normally used, in an attempt to strike a good tradeoff.

In networks with homogeneous mobility and traffic, it is known that using just a few extra copies leads to significant performance gains. For example, in a network of 1000 nodes, simply distributing 10 extra copies to the first 10 nodes encountered provides an almost 10-fold improvement in delay compared to direct transmission [5]. Although this also comes with a 10-fold increase in the amount of (storage and bandwidth) resources needed, it presents a very useful tradeoff to DTN protocol designers.

However, when it comes to heterogeneous mobility and traffic, Proposition 1 suggests that, unlike the above example, the source is no longer equivalent with other random relays, in terms of their probability of contacting an intended destination soon. It is thus of particular interest to examine whether the above trade-off still holds, if one considers the joint effect of realistic mobility and communication traffic patterns.

We thus consider, in the following, *Relay-assisted* routing, which is a simple abstraction of schemes that use extra *randomly* chosen relays[2]. To compare the performance of Relay-assisted routing and Direct Transmission, in terms of delivery delay and delivery probability (the two main metrics considered in related work), we first define the following metrics:

(a) Delay Ratio, R: the ratio of the expected delivery delay of Relay-Assisted routing, $E[T_R]$, over the expected delivery delay of Direct Transmission routing, $E[T_{DT}]$, i.e.

$$R = \frac{E[T_R]}{E[T_{DT}]}$$

(b) Source Delivery Probability, $\mathbf{P_{(src.)}}$: the probability that a message is delivered to the destination by the source node, rather than by any of the relays.

2. We will briefly consider *mobility-aware* schemes in Section 5.

Both metrics contain information about the performance gain of Relay-assisted routing compared to Direct Transmission. Specifically, R shows how faster (on average) a message can be delivered under Relay-assisted routing, whereas $P_{(src.)}$ gives the probability that any of the relays will actually contribute in the delivery process. It is easy to see that (i) R and $P_{(src.)}$ always take values in the interval $[0, 1]$, and (ii) the higher their values are, the less the gain due to relay nodes is.

For instance, when $R = 0.1$ Relay-assisted routing delivers (on average) a message 10 times faster than Direct Transmission, while a value $R = 0.5$ denotes that Relay-assisted routing is only 2 times faster. Respectively, when $P_{(src.)} = 0.1$ the probability that the source node s meets the destination d, before any other relay node meets d, is 10%, and $P_{(src.)} = 0.5$ means that this probability is 50%. In the limiting cases, when $R, P_{(src.)} \to 1$ the message is delivered to the destination by the source node itself, while when $R, P_{(src.)} \to 0$ delivery takes place (entirely) due to the relays.

In Result 1, we derive analytical expressions for these two metrics, R and $P_{(src.)}$. The proof is given in Section 8.2.

Result 1. *When Relay-assisted routing with L extra copies is considered, then*

$$R = \frac{1}{E\left[\frac{\tau(\lambda)}{\lambda}\right]} \cdot \int_0^\infty \int_0^\infty \frac{\tau(x)}{x+y} \cdot f_\lambda(x)dx \cdot f_R(y)dy$$

$$P_{(src.)} = \frac{1}{E[\tau(\lambda)]} \cdot \int_0^\infty \int_0^\infty \frac{x \cdot \tau(x)}{x+y} \cdot f_\lambda(x)dx \cdot f_R(y)dy$$

where the expectations are taken over f_λ and $f_R = f_\lambda^{(*L)}$ is the L-fold convolution of f_λ.

In addition to the main metrics considered in this paper (Result 1), and for the reader's ease of reference, in Table 1 we provide expressions for the absolute performance (message delivery delay and delivery probability) of Direct Transmission and Relay-Assisted routing. The expressions follow straight from the proof of Result 1 or through similar analysis, and, thus, we omit the detailed derivations.

3.2 Insights for Real Opportunistic Networks

The expressions we derived in Result 1 are generic and can be used under any mobility and traffic pattern (i.e. for any f_λ and $\tau(\cdot)$). However, they do not give a good feel as to how exactly these metrics are affected by mobility and traffic heterogeneity. To obtain some further insights, in this section, we consider specific classes of mobility and traffic patterns that capture commonly observed characteristics of real networks. For these classes, we derive *simple closed form expressions* that bound the performance metrics R and $P_{(src.)}$.

Mobility

We will assume the contact rates to be *gamma distributed*, i.e. $f_\lambda(x) \sim \Gamma(x; \alpha, \beta) = \frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x}$.

Our choice is initially motivated by the findings of Passarella et al. [10], who have shown, through statistical analysis

TABLE 1
Expected delivery delay and delivery probability of Direct Transmission and Relay-Assisted routing.

Direct Transmission	**Relay-Assisted**
Generic Case:	
$E[T_{DT}] = \frac{1}{E[\tau(\lambda)]} \cdot E\left[\frac{\tau(\lambda)}{\lambda}\right]$	$E[T_R] = \frac{1}{E[\tau(\lambda)]} \cdot \int_0^\infty \int_0^\infty \frac{\tau(x)}{x+y} \cdot f_\lambda(x)dx \cdot f_R(y)dy$
$P\{T_{DT} \leq t\} = 1 - \frac{E[\tau(\lambda) \cdot e^{-\lambda \cdot t}]}{E[\tau(\lambda)]}$	$P\{T_R \leq t\} = 1 - \frac{E[\tau(\lambda) \cdot e^{-\lambda \cdot t}]}{E[\tau(\lambda)]} \cdot \int_0^\infty e^{-y \cdot t} \cdot f_R(y)dy$
Mobility $f_\lambda(x) \sim \Gamma(x; \alpha, \beta)$, Traffic $\tau(x) = c \cdot x^k$:	
$E[T_{DT}] = \frac{1}{\mu_\lambda} \cdot \frac{1}{1 + (k-1) \cdot CV_\lambda^2}$	$E[T_R] \geq \frac{1}{\mu_\lambda} \cdot \frac{1}{1 + k \cdot CV_\lambda^2 + L}$
$P\{T_{DT} \leq t\} = 1 - \left(1 + \mu_\lambda \cdot CV_\lambda^2 \cdot t\right)^{-\frac{1+k \cdot CV_\lambda^2}{CV_\lambda^2}}$	$P\{T_R \leq t\} = 1 - \left(1 + \mu_\lambda \cdot CV_\lambda^2 \cdot t\right)^{-\frac{1+k \cdot CV_\lambda^2 + L}{CV_\lambda^2}}$

of pervasive social networks' datasets, that the *Gamma distribution* matches well the observed contact rates. In addition, the analytical findings of [10], further suggest that the choice of a Gamma distribution can be supported in real opportunistic networks and can explain many of the observed properties (e.g. distribution of *aggregate* inter-contact times). Finally, by selecting appropriately the parameters α and β of a Gamma distribution, we can assign *any* desired value to the mean value μ_λ and the variance σ_λ^2 of the contact rates[3]. This allows us to describe (or fit up to the first two moments) a large range of scenarios with different mobility heterogeneities captured by $CV_\lambda = \frac{\sigma_\lambda}{\mu_\lambda}$.

Traffic

We further describe the traffic using a *polynomial function* of the form $\tau(x) = c \cdot x^k$, $c > 0$.

As in the case of mobility, the reasons for our choice are as following. Observations of real networks have shown that the nodes with high contact frequencies tend to exchange more traffic [13], [14], which is consistent with the above choice when $k > 0$. Second, the exact traffic patterns (i.e. $\tau(x)$) in a real scenario are difficult (if not impossible) to determine, and, hence, it is more probable that simple methods will be used. For example, one might get some traffic samples and perform linear regression on the measured data. This would result in a linear $\tau(x)$ (i.e. $k = 1$). Our model extends this logic by going beyond linear fitting and allowing as well sub- and super-linear fitted traffic patterns. In general, the values of k capture the amount of traffic heterogeneity. Furthermore, by choosing $0 < k < 1$ (or $k > 1$) one can emulate concave (or convex) functions and, thus, approximate different traffic patterns. Finally, one can also consider negative correlations, by choosing $k < 0$. Although less common, these could arise, for example, in applications where users want to communicate more when they do not meet frequently (e.g. messaging).

Under the above assumptions, the following result for the relative performance of the information dissemination mechanisms we consider in this paper, holds. The proof of Result 2 is given in Section 8.3. The corresponding expressions for the absolute performance metrics are given in Table 1.

3. The mean value and variance of a gamma distribution are given by $\mu_\lambda = \frac{\alpha}{\beta}$ and $\sigma_\lambda^2 = \frac{\alpha}{\beta^2}$, respectively.

Result 2. *In a Heterogeneous Contact Network where $f_\lambda \sim \Gamma(\alpha, \beta)$ with mean value μ_λ and variance σ_λ^2 (coefficient of variation $CV_\lambda = \frac{\sigma_\lambda}{\mu_\lambda}$) and $\tau(x) = c \cdot x^k$, it holds:*

$$1 \geq \quad R \quad \geq \quad R_{min} = \frac{1 + (k-1) \cdot CV_\lambda^2}{1 + k \cdot CV_\lambda^2 + L} \tag{2}$$

for $k > k_{min} = 1 - \frac{1}{CV_\lambda^2}$, and

$$1 \geq \quad P_{(src.)} \quad \geq \quad P_{min} = \frac{1 + k \cdot CV_\lambda^2}{1 + (k+1) \cdot CV_\lambda^2 + L} \tag{3}$$

for $k > k_{min} = -\frac{1}{CV_\lambda^2}$.

The expressions of Result 2 depend only on 3 parameters (CV_λ, k, L) and, thus, could be used to tune Relay-Assisted schemes: At first, since mobility (CV_λ) and traffic (k) parameters are characteristics of the network, they either remain constant or change slowly over a long time period. Hence, we can assume that nodes know their values, or can estimate them (e.g. with a distributed mechanism, locally, etc.) [32], [33]. Then, the required number of relays L to achieve a certain expected delay, could be easily estimated.

***Practical Example*:** If the measured network characteristics are $CV_\lambda = 2$ and $k = 2$, then from Result 2 we get $R = \frac{5}{9+L}$. Therefore, to achieve delivery delay two times faster than Direct Transmission, one extra copy should be used ($L = 1 \rightarrow R = 0.5$), while to achieve 4 times faster delivery, $L = 11$ relay nodes are needed. In the latter case, if traffic/mobility heterogeneity has not been taken into account [5], the prediction would be $L = 3$ and this would lead only to 2.5 (instead of 4) times faster delivery (i.e. $R = \frac{5}{12}$).

3.3 Implications

It is evident from the above example that traffic heterogeneity can have a major impact on performance and thus protocol design. Table 2 formalizes this impact, by considering how R_{min} and P_{min} (Eq. (2) and Eq. (3)) behave:
The *middle column* shows their monotonicity as mobility heterogeneity (CV_λ), traffic heterogeneity (k), and amount of extra copies (L) increase. For instance, when k increases ($\nearrow$), R_{min} and P_{min} increase ($\nearrow$) too.

TABLE 2
R_{min}, P_{min}: Monotonicity and Asymptotic Limits

Parameter x	Monotonicity as parameter x increases $\nearrow$	Limits for $x \to min\{x\}$	$x \to max\{x\}$
mobility heterogeneity: $CV_\lambda \in [0, \infty)$	R_{min} increases $\nearrow$, if $k > 1 + \frac{1}{L}$; decreases $\searrow$, otherwise P_{min} increases $\nearrow$, if $k > \frac{1}{L}$; decreases $\searrow$, otherwise	$\lim\limits_{CV_\lambda \to 0} R_{min} = \mathbf{\frac{1}{1+L}}$ $\lim\limits_{CV_\lambda \to 0} P_{min} = \mathbf{\frac{1}{1+L}}$	$\lim\limits_{CV_\lambda \to \infty} R_{min} = \mathbf{1\text{-}\frac{1}{k}}$ $\lim\limits_{CV_\lambda \to \infty} P_{min} = \mathbf{1\text{-}\frac{1}{k+1}}$
traffic heterogeneity: $k \in (k_{min}, \infty)$	R_{min}, P_{min} increase $\nearrow$	$\lim\limits_{k \to k_{min}} R_{min}, P_{min} = \mathbf{0}$	$\lim\limits_{k \to \infty} R_{min}, P_{min} = \mathbf{1}$
extra copies: $L \quad (L \ll N)$	R_{min}, P_{min} decrease $\searrow$	-	

The *right column* gives their values in the limit for large/small k or CV_λ; e.g.

$$\lim_{CV_\lambda \to 0} R_{min} = \lim_{CV_\lambda \to 0} \frac{1 + (k-1) \cdot CV_\lambda^2}{1 + k \cdot CV_\lambda^2 + L} = \frac{1}{1+L}$$

and

$$\lim_{CV_\lambda \to \infty} P_{min} = \lim_{CV_\lambda \to \infty} \frac{1 + k \cdot CV_\lambda^2}{1 + (k+1) \cdot CV_\lambda^2 + L} = 1 - \frac{1}{k+1}$$

In this section, we elaborate on some important implications that follow from Table 2.

Gain of Extra Copies

A strong positive correlation (large k) between traffic and mobility reduces the added value of extra copies (i.e. R_{min}, $P_{min} \nearrow$ as $k \nearrow$). This indicates that, as correlation (k) increases, one needs to distribute message copies to more relays nodes in order to achieve a certain performance improvement compared to the baseline, Direct Transmission.

In contrast, a negative (or weak positive) correlation renders each extra copy more useful (i.e. R_{min}, $P_{min} \to 0$ as $k \to k_{min}$[4]). The fact that a *weak positive* correlation, e.g. $k \in (0, \frac{1}{L})$, actually makes extra copies more useful might be a bit surprising. However, it is explained as following: Mobility heterogeneity (when traffic is homogeneous or uncorrelated with mobility) affects negatively the message delivery delay (of random protocols and Direct Transmission) [9], [11], whereas positively-correlated traffic has an opposite effect (i.e. decreases delay). The counterbalancing effects of these two factors determine a *threshold* (e.g. $1 + \frac{1}{L}$ for R_{min} or $\frac{1}{L}$ for P_{min}) under which the negative effects of heterogeneity affect more the message delivery process. Our framework, not only reveals this inherent trade-off, but also provides the tools for quantifying such thresholds.

From the above discussion it becomes evident that it is crucial to identify whether a traffic-mobility correlation exists in a given scenario, and what its nature is, as this could decide whether the overhead of using few or more extra copies is justified or would just waste a lot of valuable resources. In practice, this means that a relay-assisted protocol should be complemented with an online estimation algorithm, collaborative or local. Such schemes have been proposed [32], [33] to collect contact related information for forwarding algorithms, but would now need to maintain also traffic-related information *and* correlate it with the information about the node contact rates, in an efficient manner.

4. The values of k_{min} are given in Result 2.

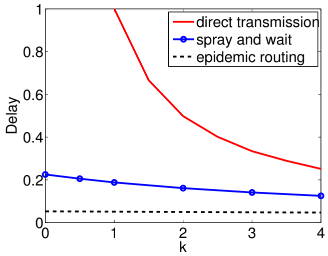
Routing for Unicast Applications

For high heterogeneity (traffic and mobility), our results imply that a unicast message is likely to arrive to its destination at the time the source and destination come *in contact* (i.e. R_{min}, $P_{min} \to 1$ as $k, CV_\lambda \to \infty$). This raises questions about the usefulness of opportunistic networking for unicast applications in which end-to-end traffic is expected to be highly correlated with contact frequency (e.g. Facebook messaging) [13], [14].

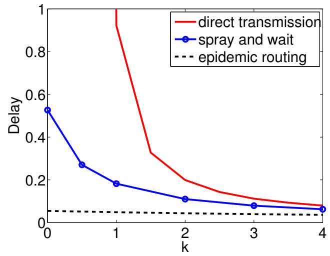
On the other hand, our results suggest that potential unicast applications with an end-to-end traffic demand between nodes with non-frequent meetings, i.e. scenarios with small or negative k, (e.g. social peers residing in different communities) could benefit a lot (more than normally assumed).

Although these observations might appear somewhat self-evident at first glance (note however the case described in the previous subsection), the question of how to tune protocols and choose the right number of replicas stills remains. To our best knowledge, our results are the first to provide closed form, *quantitative* insights into the tradeoffs involved in real scenarios with both mobility and traffic heterogeneity.

Moreover, one could raise a point about their applicability for sophisticated protocols that choose relays intelligently (e.g. based on contact rates, social graphs). In this case, a source node could try to wait and select better relays than giving the copies to the first randomly encountered peers, thus improving the impact per replica. Nevertheless, in a highly heterogeneous scenario, a source might need to wait a long time until it encounters such good relays ("spray" phase) and this could counter-balance the effect of better relays. In Section 5, we prove that the qualitative implications of our results hold also for such mobility-aware protocols, which exploit mobility heterogeneity in order to select better relays. A complementary explanation for this qualitative result is given in the end of this section (see Fig. 2 and the corresponding commentary).



(a) $CV_\lambda = 1$



(b) $CV_\lambda = 2$

Fig. 2. Message delay under Direct Transmission, Spray and Wait ($L = 5$), and Epidemic routing in scenarios with varying traffic heterogeneity; mobility parameters are $\mu_\lambda = 1$ and (a) $CV_\lambda = 1$ and (b) $CV_\lambda = 2$.

Content-Centric Communication

While our results are somewhat pessimistic when it comes to the usefulness of opportunistic networking for unicast applications, the opposite holds when it comes to modern, content-centric applications (e.g. file sharing, D2D-based offloading, service composition). In such applications nodes are looking, for example, for some content of interest [3] or service [2], which they can access directly from *any* encountered node that offers it. If the interests of nodes are heterogeneous (which is known to be the case [34]) and nodes with similar mobility patterns tend to have *some* similarity in their interests too (evidence for this does exist [35]), then our results suggest: (i) that there is a better chance to find a content or service "soon" from a directly encountered node than one would expect in homogeneous scenarios, and (ii) coming up with complex, resource-costly mechanisms, e.g. multi-hop query-response, directories, etc., might not be necessary. We plan to look into such content-centric scenarios in more detail in future work.

To put some extra evidence on our arguments and further demonstrate *how* and *why* traffic heterogeneity affects the relative performance, in Fig. 2 we compare the message delay of (i) Direct Transmission (i.e. the protocol with the *highest* delay), (ii) Relay-assisted routing (Spray and Wait, *SnW*, [5] with $L = 5$ copies) and (iii) Epidemic routing [15] (i.e. the protocol with the *lowest* delay), in two scenarios, for varying traffic heterogeneity (k). Two main observations, with respect to the previous implications, can be made in Fig. 2.

At first, an increasing amount of traffic heterogeneity/correlation closes the performance gap between the best (Epidemic) and the worst (Direct Transmission) forwarding policies. Hence, it becomes evident that the possible gain one could achieve by using *any routing protocol* and *any number of extra copies*, diminishes. As a result, routing schemes, whose design is crucial in homogeneous scenarios (since the improvement gap is large; see Fig. 2 for regions with low k), become less important in heterogeneous scenarios with highly correlated traffic (since the improvement cannot be large; see Fig. 2 for regions with high k) and/or less necessary (since comparable performance can be achieved with Direct Transmission; e.g. Fig. 2(b) for $k = 4$).

Second, the delay of Direct Transmission decreases radically as traffic heterogeneity increases[5]. Although the delay of Relay-assisted routing decreases with traffic heterogeneity k too, the effect is less significant. Specifically, an observation of the delay curves for Direct Transmission and Relay-assisted routing in Fig. 2(a), shows that the delay ratio $R = \frac{E[T_R]}{E[T_{DT}]}$ increases as traffic becomes more heterogeneous. However, this increase is mainly due to the *improved performance of Direct Transmission* rather than this of Relay-assisted routing.

4 Model Validation

To validate our model and analysis, in this section we compare the theoretical results against Monte Carlo simulations on various synthetic scenarios, and on datasets of real networks.

4.1 Synthetic Simulations

We generate synthetic networks, conforming to the mobility and traffic models of Section 2, as following:
(i) We assign to each pair $\{i, j\}$ a contact rate λ_{ij}, which we draw randomly from f_λ, and create a sequence of contact events (Poisson process with rate λ_{ij}).
(ii) Since $E[\tau_{ij}] = \tau(\lambda_{ij})$ (from Def. 2), we draw the traffic rate for each pair $\{i, j\}$ as $\tau_{ij} \sim Uniform[0, 2 \cdot \tau(\lambda_{ij})]$.
(iii) Then, we simulate a large number of message exchanges, choosing randomly for each message the source-destination pair according to the weights τ_{ij}.

We created different scenarios $(N, L, f_\lambda, \tau(\cdot))$ to verify our analysis under various network parameters. Here, we present the simulation results for scenarios with $N = 500$ nodes[6]. As Relay-assisted routing, we used the *Spray and Wait* protocol [5] with $L = 5$ copies. To be consistent with the analysis of Section 3.2, we used the *Gamma distribution* as the contact rates distribution f_λ and traffic functions of polynomial form, $\tau(x) = c \cdot x^k$.

In Fig. 3 and Fig. 4 we present simulation results for the ratios R and probabilities $P_{(src.)}$, along with the corresponding theoretical results (exact predictions of Result 1 and lower bounds of Result 2), in scenarios with varying mobility and traffic heterogeneity.

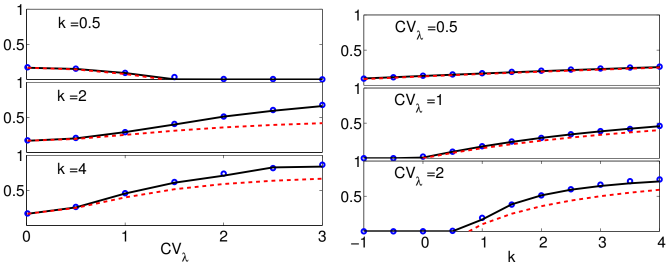
Fig. 3 shows the *delay ratio* R: (a) in three scenarios with different traffic functions $\tau(x)$ (namely[7]: $c \cdot \sqrt{x}$, $c \cdot x^2$, and $c \cdot x^4$), under varying *mobility* heterogeneity; and (b) in three mobility scenarios with $CV_\lambda = \{0.5, 1, 2\}$, under varying *traffic* heterogeneity. A first observation is that the exact expressions of Result 1 (continuous lines) can accurately predict the metric R (simulation results are denoted with circles). Additionally, the lower bounds are always below the simulation curves (as expected), and in many scenarios are quite tight.

Under the same mobility (CV_λ) and traffic (k) simulation scenarios, similar observations can be made for the *source*

5. The convergence is faster for scenarios where node mobility is more heterogeneous (Fig. 2(b)), suggesting, thus, that the effects of traffic heterogeneity are even more important when coupled with highly heterogeneous node mobility.

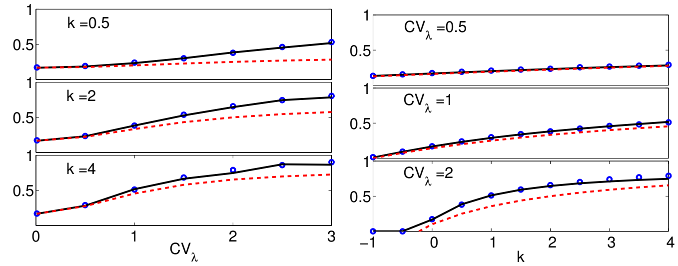
6. The simulations we ran for networks with $N \in [100, 1000]$ nodes, gave us similar results.

7. The value of c does not affect the performance (see also Result 2).



(a) $R = \frac{E[T_R]}{E[T_{DT}]}$ vs. CV_λ (b) $R = \frac{E[T_R]}{E[T_{DT}]}$ vs. k

Fig. 3. R in scenarios with varying (a) mobility and (b) traffic heterogeneity. Simulation results are denoted with circles; the theoretical predictions of Result 1 (exact predictions) with continuous lines; and the lower bounds R_{min} (Result 2) with dashed lines.



(a) $P_{(src.)}$ vs. CV_λ (b) $P_{(src.)}$ vs. k

Fig. 4. $P_{(src.)}$ in scenarios with varying (a) mobility and (b) traffic heterogeneity. Simulation results are denoted with circles; the theoretical predictions of Result 1 (exact predictions) with continuous lines; and the lower bounds P_{min} (Result 2) with dashed lines.

delivery probability $P_{(src.)}$ in Fig. 4, where the exact expressions of Result 1 accurately match the simulation results and the bounds of Result 2 are tight in most scenarios.

In general, for both the metrics R and $P_{(src.)}$, the theoretical lower bounds are less tight for scenarios where mobility is quite heterogeneous. Specifically, in Fig. 3(a) and 4(a), the bounds are less close to the simulation curves in the regimes where CV_λ becomes larger than 2. Also, in the scenarios with varying traffic heterogeneity (Fig. 3(b) and 4(b)), the bounds are tight for scenarios with small and moderate mobility heterogeneity, and become less tight only in the scenarios with $CV_\lambda = 2$ (bottom plots of Fig. 3(b) and 4(b)).

In every scenario, the simulation curves R and $P_{(src.)}$ have the monotonicity we predicted in Table 2 (middle column) for the theoretical bounds R_{min} and P_{min}. For instance, when traffic heterogeneity (k) increases, R and $P_{(src.)}$ always increase as well (Fig. 3(b) and 4(b)). Also, in the regimes that $k \leq k_{min}$[8] the simulation values of the considered metrics become almost zero, and for large k (especially in the bottom plots of Fig. 3(b) and 4(b), where mobility is also very heterogeneous) they get close to 1, thus validating the qualitative predictions of Table 2 (right column).

The simulation results in Fig. 3(a) and 4(a), where we present scenarios with varying mobility heterogeneity (CV_λ), validate our predictions for the monotonicity and limiting behavior as well. For example, in Fig. 3(a) for $k = 0.5$, where the traffic-mobility correlation is small (the same holds also for negative correlations), R and R_{min} decrease as the mobility heterogeneity increases (as suggested in Table 2). In the rest of the plots, the bounds and the corresponding simulated values increase, demonstrating that the gain of the extra copies diminishes under such conditions, and, thus, confirming our qualitative results (Section 3.3). For example, in the bottom plot ($k = 4$) of Fig. 3(a), we can see that the improvement offered by the extra relays is at most $6\times$ (since $R = \frac{1}{1+L} = \frac{1}{6}$) for homogeneous network ($CV_\lambda = 0$), while for $CV_\lambda > 2$ the extra gain is at most $1.25\times$ (since $R > 0.8$); that is, even using 5 relays will only marginally improve the delay. Similarly, from Fig. 4(b) and for $CV_\lambda = 2$, we can see that, while for almost homogeneous traffic ($k < 0.5$) the probability of the message being delivered through direct transmission, $P_{(src.)}$, gets less than 40%, when traffic becomes very heterogeneous ($k \geq 4$), this probability is around 80%.

8. (i) $k_{min} = 0$ and $k_{min} = 0.75$ for the middle ($CV_\lambda = 1$) and bottom ($CV_\lambda = 2$) plots in Fig. 3(b), respectively; and (ii) $k_{min} = -1$ and $k_{min} = -0.25$ for the middle ($CV_\lambda = 1$) and bottom ($CV_\lambda = 2$) plots in Fig. 4(b), respectively.

TABLE 3
Datasets Information

Dataset	Nb of Nodes	Contacts	Traffic
Gowalla/Twitter	(AU) 1004 (SF) 479	Check-ins	Tweets
Strathclyde	24	Bluetooth Proximity	Calls/SMS

4.2 Real-World Networks

To further investigate the applicability of our results in real-world networks, we conduct simulations on datasets collected from online social networks (*Gowalla / Twitter* dataset [13]) and a mobile phone usage experiment (*Strathclyde* dataset [36]). In the following discussion we present the datasets, whose main features can be found also in Table 3.[9]

Gowalla / Twitter dataset

Gowalla was a location-based social network, where users were able to *check-in* at ”spots” (bars, shops etc.) through their mobile phones. In addition, a user could connect her Gowalla account to her Twitter account. Hence, from this dataset, we could retrieve information related both to nodes' mobility (Gowalla *check-ins*) and communication traffic (*tweets*).

Mobility: In this dataset, we consider as a contact event the time when two users reside in the same ”spot” simultaneously[10]. The contact rates λ_{ij} can be computed from the

9. Here, we need to stress that the selected datasets are not necessarily characteristic examples of opportunistic networking; e.g., Gowalla is a very sparse dataset in terms of node contacts, and phone calls (*Strathclyde*) is not considered among the main opportunistic applications. However, they are some of the few available datasets containing the type of data we needed (i.e. both mobility and traffic information), and, thus, this was our best option for a realistic validation.

10. Since Gowalla users only check in and do not check out, we cannot infer directly this information. Therefore, following the methodology of [13], we assumed that each user remains at a spot she visited for 1 hour.

number of the contact events and the inter-contact time intervals. Then, to incorporate this information in our model, we fit the contact rates distribution f_λ with a known probability distribution $\hat{f}_\lambda$. Specifically, in the two cities, Austin (AU) and San Francisco (SF), for which we have the most user records (1004 and 479 nodes, respectively), the experimental CCDF (*complementary cumulative distribution function*) of the contact rates λ_{ij} can be approximated by a straight line on a log-log plot. This implies that f_λ could be fitted with a *Pareto* distribution, instead of the Gamma distribution assumed in Section 3.2 and often observed in traces. Therefore, we use here the expressions of Result 1, instead of Result 2.

Communication Traffic: As an indication for the communication traffic that two nodes would exchange in an opportunistic network, we use the number of *tweets* in which they are both involved. Hence, for each pair $\{i, j\}$ we set its traffic rate τ_{ij} equal to the number of tweets posted by i to j or by j to i, i.e. $\tau_{ij} = \#tweets_{ij}$. Then, we approximate the observed relation between traffic and contact rates ($\tau_{ij} \sim \lambda_{ij}$) with a function $\hat{\tau}(x)$, in order to use it in our theoretical expressions. We also investigate more possible correlations between the opportunistic traffic (τ_{ij}) and the Twitter traffic ($\#tweets$), by creating two additional scenarios where we set $\tau_{ij} = \sqrt{\#tweets_{ij}}$ and $\tau_{ij} = (\#tweets_{ij})^2$. The approximative functions $\hat{\tau}(x)$ for each scenario are presented in Table 4, where we can see $\hat{\tau}(x)$ being of type $c \cdot x^k$ with $k < 1$.

Strathclyde dataset

The Strathclyde dataset was collected in an experiment, in which 24 high school students were selected and given modified smartphones, which recorded proximity events (through Bluetooth), calls and sms exchanged between the phone user and the other participants.

Mobility: In this dataset the contact events were already recorded and, thus, we did not have to preprocess the data as in the Gowalla dataset. We followed the same methodology to calculate the contact rates λ_{ij} and fit their distribution with a *Gamma* distribution, denoted as $\hat{f}_\lambda$.

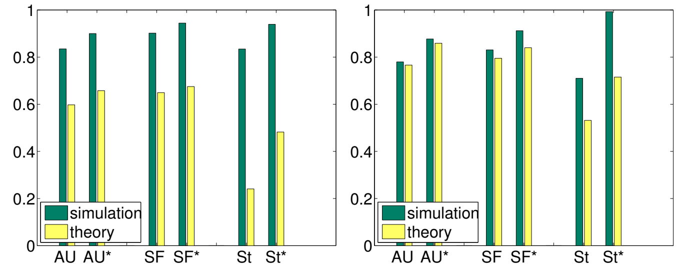
Communication Traffic: We consider three scenarios, in each of which we use a different communication traffic metric: (i) total number of calls and sms, $\tau_{ij} = \#calls_{ij} + \#sms_{ij}$, (ii) total duration of calls, $\tau_{ij} = callTime_{ij}$, and (iii) total length of sms (in characters), $\tau_{ij} = smsLength_{ij}$. For each scenario, we fit function $\hat{\tau}(x)$ as before, through the relation $\tau_{ij} \sim \lambda_{ij}$.

Simulations

In both datasets and for each traffic scenario, we generate 10000 messages at random time points, choosing each time the source - destination pair according to the weights τ_{ij}. We consider Direct Transmission and Spray and Wait routing [5] with $L = 2, 5, 10, 20$ copies per message. In the analytical expressions we use the fitted functions $\hat{f}_\lambda(x)$ and $\hat{\tau}(x)$.

TABLE 4
Fitting traffic functions for the Gowalla dataset

Scenarios:	S1	S2	S3
τ_{ij}	$\sqrt{\#tweets_{ij}}$	$\#tweets_{ij}$	$(\#tweets_{ij})^2$
$\hat{\tau}(x)$ (AU)	$c \cdot x^{0.6}$	$c \cdot x^{0.83}$	$c \cdot x^{0.79}$
$\hat{\tau}(x)$ (SF)	$c \cdot x^{0.31}$	$c \cdot x^{0.35}$	$c \cdot x^{0.37}$



(a) $R = \frac{E[T_R]}{E[T_{DT}]}$ (b) $P_{(src.)}$

Fig. 5. Simulation results for R and $P_{(src.)}$ and theoretical predictions for homogeneous and heterogeneous ($*$) traffic scenarios on the datasets.

In Fig. 5 we present the simulation values for the ratio R and the probability $P_{(src.)}$ (green/left bars), and the corresponding theoretical predictions (yellow/right bars). We consider *homogeneous* and *heterogenous* (denoted with $*$) traffic scenarios in the Gowalla/Twitter (*AU* and *SF*) and Strathclyde (*St*) datasets. The first observation is that in all scenarios, for heterogeneous traffic (i.e. scenarios denoted with $*$), the values of the metrics R and $P_{(src.)}$ increase, compared to the corresponding homogeneous scenarios. This shows that the relative gains of relay-assisted schemes decrease with traffic heterogeneity, as our theoretical results predict. Moreover, larger performance differences predicted by our theory, are matched by larger performance differences in the respective simulation scenarios as well. For example, in the *SF* scenarios (middle bars in Fig. 5(a) and Fig. 5(b)), the theoretical predictions for heterogeneous traffic are slightly higher than for the homogeneous case; the same holds also for the simulation results, where it can be seen that R and $P_{(src.)}$ do not significantly increase with traffic heterogeneity. On the other hand, in the *St* scenarios (right bars in Fig. 5(a) and Fig. 5(b)), our results predict a higher difference (between heterogeneous and homogeneous cases) than before, which is also confirmed by the simulation results where the performance effects are not negligible.

To further demonstrate to what extent our results can capture the effect of traffic heterogeneity in real scenarios, in Table 5 we focus on the qualitative predictions of our theory, by comparing a number of scenarios with different amounts of heterogeneity to each other, for the Gowalla/Twitter dataset[11]. Specifically, if the simulated performance improves from one scenario to another, and so is the theoretical prediction, the prediction is assumed to be correct and denoted with ✓. "Incorrect" predictions are denoted with ×. For example, in the scenarios *AU-S1* and *SF-S3* the simulation values for the ratios R are $R^{(AU-S1)} = 0.89$ and $R^{(SF-S3)} = 0.94$, i.e. $R^{(AU-S1)} < R^{(SF-S3)}$. For the theoretical predictions it holds also that $R^{(AU-S1)} = 0.64 < R^{(SF-S3)} = 0.68$ and, thus, the prediction is assumed to be correct. The elements

11. We denote with *S1*, *S2* and *S3* the corresponding scenarios presented in Table 4 and with *HOM* the scenarios with homogeneous traffic.

TABLE 5
Comparison of predictions for the metrics R and $P_{(src.)}$ between different scenarios on the Gowalla dataset

*	R	AU			SF		
$P_{(src.)}$	*	HOM	S1	S2	HOM	S1	S3
AU	HOM	*	✓	✓	✓	✓	✓
	S1	✓	*	✓	✓	✓	✓
	S2	✓	✓	*	×	✓	✓
SF	HOM	✓	✓	✓	*	✓	✓
	S1	✓	✓	×	✓	*	✓
	S3	✓	✓	×	✓	✓	*

above the diagonal refer to the ratio R, whereas the lower triangular part refers to the probability $P_{(src.)}$ predictions.

It is evident that in the majority of the cases we consider, the theoretical results can capture the relative changes in network performance, even between different environments (i.e. between *AU* and *SF*)[12]. The same conclusions can be reached by the analysis in the Starthclyde dataset, in which *all* the respective comparisons were found to be correct ✓.

5 Extensions

We have tried to present our results in the context of simple schemes (e.g. unicast traffic, random relay selection), to keep analysis tractable and illustrate key principles. In this section, we discuss how our framework could be applied in some additional cases. Although far from complete, we believe this set of examples, further underlines the utility of our analysis.

5.1 Mobility-Aware Protocols

Mobility-aware schemes are often used to select good relays for the intended replicas, rather than picking random ones, e.g. [6], [7], [16], [37]. The selection of the relays is usually based on their social or mobility characteristics. For instance, in *encounter-based routing (EBR)* [16], the more frequently a node i encounters node d, the higher the probability to become a relay of a message destined to d.

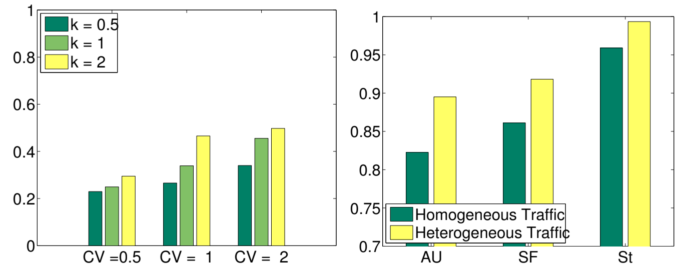
The relay-selection mechanism in a number of proposed mobility-aware protocols can be described as following:

Definition 3. *The probability p_i a node i to be selected as a relay for a message destined to node d, is related to their contact rate λ_{id} and this relation is described by a function $p(\lambda_{id})$.*

As an example, we present two protocols belonging to the above class and their $p(\lambda)$ functions: (a) a modified mobility-aware version of *spray and wait* [5] protocol (we refer to it as *U1*), and (b) a variation of the *EBR* [16] protocol (we refer to it as *U2*), where each relay can hold only one message copy.

U1: A node i, which would be selected as a relay by the *spray and wait* mechanism, under *U1* becomes a relay with a probability p_i that is proportional to its contact rate with the destination d, i.e. $p_i = p(\lambda_{id}) = c \cdot \lambda_{id}$, where c a normalizing factor such as $p(\lambda) \in [0, 1]$.

12. Differences in simulation and theoretical results between different heterogeneous scenarios of the same traces, are very small (due to the dataset limitations), and that is also the main reason for some × entries in Table 5.



(a) Synthetic scenarios (b) Real networks

Fig. 6. $P_{(src.)}$ of mobility-aware routing in (a) synthetic scenarios with varying mobility (CV_λ) and traffic heterogeneity (k), and (b) real networks with homogeneous and heterogeneous traffic.

U2: For each message copy, the source node s selects the relay node i with a probability p_i that is computed according to the *EBR* mechanism, i.e. $p_i = p(\lambda_{id}) = \frac{\lambda_{id}}{\lambda_{id}+\lambda_{sd}}$.

In the following corollary, we prove that our Results 1 and 2 can be simply modified and capture such mobility-aware protocols as well. Corollary 1 follows from a similar analysis as in Section 3, whose main analytical steps are described in Section 8.5.

Corollary 1. *Under a mobility-aware Relay-Assisted protocol conforming to Definition 3, Results 1 and 2 are modified as: Result 1: f_R is given by the L-fold convolution of $f_u(\lambda)$, where*

$$f_u(x) = \frac{1}{E[p(\lambda)]} \cdot p(x) \cdot f_\lambda(x)$$

Result 2: The number of copies L is multiplied by c_u, where

$$c_u = \frac{E[\lambda \cdot p(\lambda)]}{E[\lambda] \cdot E[p(\lambda)]}$$

For instance, applying Corollary 1, the expression for the delay ratio R, becomes

$$1 \geq \quad R \quad \geq \quad R_{min} = \frac{1 + (k-1) \cdot CV_\lambda^2}{1 + k \cdot CV_\lambda^2 + c_u \cdot L} \tag{4}$$

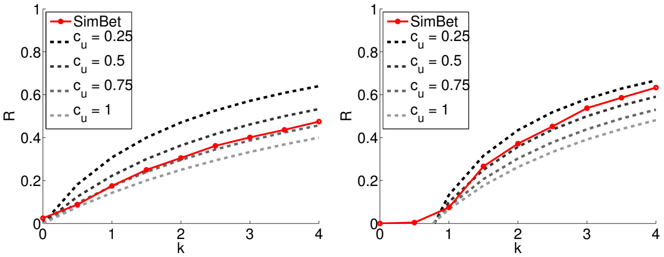
and for the *U1* protocol presented above, c_u is given by the expression[13]:

$$c_u^{(U1)} = 1 + CV_\lambda^2 \tag{5}$$

When mobility is highly heterogeneous (i.e. high CV_λ), $c_u^{(U1)}$ becomes large, and thus R_{min} and P_{min} decrease compared to the random replication mechanism (e.g. random *SnW*). This confirms that the performance gain is larger when mobility-aware protocols are used. However, even in this case, as traffic heterogeneity increases, the performance gain diminishes, i.e. $R_{min}, P_{min} \to 1$.

We further demonstrate some preliminary simulation results suggesting that our conclusions hold also for mobility-aware routing. We use the *U2* protocol presented above. In Fig. 6(a) we present simulation results for the delivery metric $P_{(src.)}$

13. An expression for c_u in the case of the *U2* protocol could also be derived, albeit with more complexity, due to the fact that the function $p(\lambda)$ involves the source destination contact rate λ_{sd} as well.



(a) $CV_\lambda = 1$ (b) $CV_\lambda = 2$

Fig. 7. Delay ratio R in two scenarios with varying traffic heterogeneity k. Relay-assisted routing is SimBet with (a) $L = 5$ and (b) $L = 10$ message copies.

on synthetic scenarios with varying mobility (CV_λ) and traffic (k) heterogeneity. Similarly to the random replication case, for increasing heterogeneity (in mobility and/or traffic) the gain of the extra copies clearly decreases (i.e. $P_{(src.)}$ increases) under mobility-aware schemes. In Fig. 6(b) we compare the probability $P_{(src.)}$ of scenarios with and without traffic heterogeneity in real networks. As before, the results are consistent with our theory: the gain of extra copies decreases even for protocols using more sophisticated techniques for relay selection.

Routing based on Contact Graph Structure

A number of mobility-aware routing schemes, e.g. SimBet [7], BubbleRap [6], are based on the structure of the contact graph (centrality, similarity, communities, etc.) rather than the pairwise contact rates. A direct mapping to a function $p(\lambda)$ for these protocols requires a separate, and rather cumbersome analysis for each such protocol, in most cases not leading to a closed form expression (see, e.g. [12]). However, the contact graphs used to make forwarding decisions by these more sophisticated protocols, still are built based on pair-wise contact rates [38]. We thus expect the utility of such mobility-related information to be similarly affected by the amount of traffic heterogeneity and its relation to mobility patterns.

To test this further, we simulated, as an example, scenarios using the SimBet protocol [7][14]. In Fig. 7 we present the simulation results (continuous lines) for the ratio $R = \frac{E[T_{SimBet}]}{E[T_{DT}]}$ and the theoretical predictions R_{min} of Eq. (4), for different values of the c_u parameter (dashed lines). Two main observations that confirm our intuition are: (i) simulated and theoretical curves increase in a similar manner, and (ii) one can find (numerically) the value c_u that more accurately predicts the performance.

Although this is clearly not conclusive for the applicability of our result to every mobility-aware scheme, we believe it helps to corroborate our findings for the interplay between mobility and traffic heterogeneity on protocol performance.

5.2 Multicast Communication

We have also been assuming unicast messages between a $\{s, d\}$ pair. However, our results apply also to multicast [17]

14. For the contact graph we considered the 10% most frequently meeting pairs following the guidelines of [38], we set the similarity and betweenness weights $\alpha = \beta = 0.5$ [7], and we generated multiple copies as in [39].

TABLE 6
Multicast Communication

	CV_λ	0.1	0.5	1	1.5	2
HOM	R	0.18	0.12	0.01	0	0
	$P_{(src.)}$	0.01	0.01	0.01	0.01	0.01
HET	R	0.18	0.26	0.39	0.52	0.61
	$P_{(src.)}$	0.01	0.03	0.12	0.26	0.41

or anycast (e.g. content sharing or service composition applications) [2] messages from s, with d being one of the destinations, since similar mechanism are often used for their dissemination. To demonstrate this, in Table 6 we present simulation results for two multicast scenarios, with homogeneous (*HOM*) and heterogeneous (*HET*) traffic ($\tau(x) = c \cdot x^4$), under varying mobility heterogeneity. A source sends messages to 5 destinations (each selected with a probability $\propto \tau_{ij}$) either by Direct Transmission or by Relay-Assisted routing with $L = 5$ copies. As delivery delay, we consider the delay till all the destinations get the message. It is evident that R and $P_{(src.)}$ (i) increase significantly with mobility heterogeneity when traffic is heterogeneous, and (ii) become much larger compared to the homogeneous case (where R decreases and $P_{(src.)}$ is constant), which is in agreement with our results.

6 Related Work

Useful implications for opportunistic networking have arisen from the investigation of *mobility/social ties* and *social ties/communication traffic* correlations, which have been studied extensively and under different disciplines, like anthropology [29], sociology [28], social media [25] or pervasive social networks [10]. For example, [25] shown that the amount of exchanged communication traffic between users of OSNs depends on their social relationships.

On the other hand, the *communication traffic / mobility* correlation has not been given similar attention. There exist only a few works [13], [14] studying it in a framework relevant to opportunistic networking. In [13], Hossmann *et al.* collected and analysed two datasets from online social networks (Facebook and Gowalla / Twitter), and investigated the relations among three dimensions: *mobility, social ties, communication traffic*. With respect to our study, they found that there is strong dependence between mobility and traffic, and, specifically, node pairs that contact during the experiments' duration, communicate with higher probability than the other pairs. Correspondingly, authors in [14] analysed a massive dataset of Call Detail Records (CDRs) of 6 million users and shown a positive correlation between the mobility and communication traffic patterns. Not only they shown that the higher the contact rate (λ_{ij}) of a node pair is, the higher the probability that the nodes communicate intensively, but also found that information inferred by the mobility patterns can work as a good predictor for future communication events. However, despite the fact that [13], [14] show clearly that communication traffic is heterogeneous (and correlated to mobility), to our best knowledge, its *effects* on communication performance have not been studied previously.

Finally, with respect to our results and the insights obtained from them, it has already been observed [37], [40] that realistic mobility patterns (e.g. locality, community) can hurt the performance of Relay-Assisted routing (especially simple, random protocols [5]). However, this is a performance degradation that is due to the relays being *too similar* to the source (e.g. all in the same community [37] or with common characteristics [40]). Instead, the *relative* performance degradation here comes due to the source and relays being *too different* in terms of their encounter rates with the destination.

7 Conclusions

Motivated by (i) recent findings indicating heterogeneous traffic patterns in mobile social networks and (ii) the lack of related studies, in this paper, we modelled traffic heterogeneity and studied how it affects the performance in opportunistic networking. We found that the effects can be significant, changing our understanding of common design principles, such as the added value of relays. Despite the fact that some of our qualitative conclusions seem to be rather intuitive, they have not attracted any focus in previous studies, where performance analysis of communication schemes is conducted assuming homogeneous traffic. This indicates a necessity for revisiting the evaluation of protocols in scenarios that entail diversity in the traffic exchanged between nodes. Moreover, our results have some interesting implications about the usefulness of opportunistic networking for various applications.

We believe that our study provides an initial understanding on the effects of traffic heterogeneity. However, traffic patterns in real networks might have much more complex characteristics than what can be captured by our framework, e.g. time-dependent traffic/mobility correlations. Therefore, for a more complete characterisation of traffic demands in opportunistic networking (either for end-to-end or content-centric applications [2], [3]), we believe that further experimental (e.g. measurements, recognition of traffic patterns in available datasets, etc.) and analytical research is needed.

8 Proofs of Theoretical Results

8.1 Proof of Proposition 1

Proof: Consider a network $\mathcal{N}$ with N nodes. Let $d\lambda = O\left(\frac{1}{N}\right)$, and define the set of nodes with contact rate $\lambda_{ij} \in [\lambda, \lambda + d\lambda)$:

$$\mathcal{N}(\lambda) = \{\{i,j\} : i,j \in \mathcal{N}, \lambda \leq \lambda_{ij} < \lambda + d\lambda\},$$

The total number of messages generated per time unit between pairs $\in \mathcal{N}(\lambda)$ is equal to

$$T(\lambda) = \textstyle\sum_{\{i,j\}\in\mathcal{N}(\lambda)} \tau_{ij} \tag{6}$$

where τ_{ij} in the sum are i.i.d. random variables with mean $\tau(\lambda)$. Then, the probability that the contact rate λ_{sd}, between the source and the destination of a randomly selected message, is in $[\lambda, \lambda + d\lambda)$, is given by

$$P\{\lambda \leq \lambda_{sd} < \lambda + d\lambda\} = \frac{T(\lambda)}{\sum_i \sum_j \tau_{ij}} = \frac{\sum_{\{i,j\}\in\mathcal{N}(\lambda)} \tau_{ij}}{\sum_i \sum_j \tau_{ij}} \tag{7}$$

We can express Eq. (7) as following:

$$P\{\lambda \leq \lambda_{sd} < \lambda + d\lambda\} = \frac{T(\lambda)}{\|\mathcal{N}(\lambda)\|} \cdot \frac{\|\mathcal{N}(\lambda)\|}{N(N-1)/2} \cdot \frac{N(N-1)/2}{\sum_i \sum_i \tau_{ij}}$$

where $\|\cdot\|$ denotes the cardinality of a set and $\frac{N(N-1)}{2}$ is the total number of node pairs in a network with N nodes. Let us further denote:

$$X_1 = \frac{T(\lambda)}{\|\mathcal{N}(\lambda)\|},\ X_2 = \frac{\|\mathcal{N}(\lambda)\|}{N(N-1)/2},\ X_3 = \frac{\sum_i \sum_i \tau_{ij}}{N(N-1)/2}$$

Applying the weak law of large numbers [41], it holds that for a *large network*[15]

$$X_1 \xrightarrow{p} \tau(\lambda) \quad \text{and} \quad X_2 \xrightarrow{p} f_\lambda(\lambda) \tag{8}$$

where $\xrightarrow{p}$ denotes convergence in probability.

Also, X_3 corresponds to the sample average of τ_{ij} over all disjoints sets $\mathcal{N}(\lambda)$. Thus, applying Cramér's theorem (*Theorem 6.5* in [41])[16] and using the convergence expressions of Eq. (8), we can get

$$X_3 \xrightarrow{p} \textstyle\int_0^\infty \tau(y) f_\lambda(y) dy = E[\tau(\lambda)] = C$$

Similarly, using Cramér's theorem, it can be shown that the expression $X_1 \cdot X_2 \cdot \frac{1}{X_3}$ converges too, i.e.

$$X_1 \cdot X_2 \cdot \frac{1}{X_3} \xrightarrow{p} \tau(\lambda) \cdot f_\lambda(\lambda) \cdot \frac{1}{C}$$

Finally, denoting the probability density function of the source-destination contact rate λ_{sd} as $f_\tau(\lambda)$, i.e. $P\{\lambda \leq \lambda_{sd} < \lambda + d\lambda\} = f_\tau(\lambda) d\lambda$ gives us the desired result. □

8.2 Proof of Result 1

8.2.1 Delay Ratio, R

Proof: Let $I_{sd}(t)$ be an indicator random variable that is equal to 1 if nodes s and d are within transmission range at time t, and 0 otherwise. Let further T_{sd} denote the random inter-contact time between node pair $\{s,d\}$:

$$T_{sd} = \inf\{t > 0 : I_{sd}(0) = 1, I_{sd}(0^+) = 0, I_{sd}(t) = 1\}.$$

Since we have assumed that contact duration is negligible (Assumption 3 of Def.1), the contact process is essentially a point process, and the above could be simplified to $T_{sd} = \inf\{t > 0 : I_{sd}(0) = 1, I_{sd}(t) = 1\}$.

Assume now that end-to-end messages between $\{s,d\}$ are generated at random times and *independently* from the contact process. If T_{DT} denotes the delay of directly transmitting a message from s to d, and the contact rate between s and d is $\lambda_{sd} = x$, then one can use renewal-reward theory [42] to show that

$$E[T_{DT}|\lambda_{sd} = x] = E[T_{sd}^{(e)}|\lambda_{sd} = x] = \frac{1}{x}.$$

That is, the expected delay of direct transmission is equal to the mean of the *residual* (or *excess*) inter-contact time $T_{sd}^{(e)}$, which is an exponential variable with the same rate x.

15. When $N \to \infty$, then $d\lambda = O\left(\frac{1}{N}\right) \to 0$, and $\|\mathcal{N}(\lambda)\| = O\left(\frac{N(N-1)}{2} d\lambda\right) = O(N) \to \infty$.

16. Equivalently, one could use here the *Continuous Mapping Theorem*.

Using the property of conditional expectation and the distribution of λ_{sd} (Proposition 1) we can get:

$$E[T_{DT}] = \int_0^\infty E[T_{DT}|\lambda_{sd} = x] f_\tau(x)dx = \int_0^\infty \frac{1}{x} f_\tau(x)dx$$
$$= \frac{1}{C}\int_0^\infty \frac{\tau(x)}{x} f_\lambda(x)dx = \frac{1}{E[\tau(\lambda)]}\cdot E\left[\frac{\tau(\lambda)}{\lambda}\right] \quad (9)$$

Assume now that the same messages, between $\{s,d\}$ are routed using Relay-Assisted routing, with L message copies given to L relays. Let T_R^* denote the *total* delay to deliver a message using Relay-Assisted routing, T_R the remaining delay after all L copies have been distributed, T_{fwd} the time to distribute the L copies to the L relays, and $p_{fwd} = P(T_R^* < T_{fwd})$ the probability that the message is delivered to the destination before L relay nodes have been found.

Since relays are selected randomly (e.g. [5]), $p_{fwd} = \frac{L}{N} \to 0$ for $L \ll N$. Similarly, if $L^2 \ll N$, $\frac{T_{fwd}}{T_R} \to 0$ [5]. We can thus focus only on T_R, the time after L relays have received a copy.

Denote now with $\mathcal{L}$ the set of selected relays. Using a similar argument as in the direct transmission case, and Assumption 1 of Def.1 we can easily show that,

$$T_R \equiv \min_{i\in\mathcal{L}\cup\{s\}} T_{id} \sim exp(X_r)$$
$$X_r = \lambda_{sd} + \textstyle\sum_{i\in\mathcal{L}}\lambda_{id} = \lambda_{sd} + X_R$$

where $X_R = \sum_{i\in\mathcal{L}}\lambda_{id}$, and the expected value of T_R will be

$$E[T_R] = \frac{1}{X_r} = \frac{1}{\lambda_{sd}+X_R}, \quad (10)$$

where $\lambda_{sd} \sim f_\tau$ (Proposition 1) and $X_R \sim f_R = f_\lambda^{(*L)}$, the L-fold convolution of f_λ.

Then, from Eq. (10) and using the property of conditional expectation, we find:

$$E[T_R] = \int_0^\infty\int_0^\infty E\left[T_R|\lambda_{sd} = x, X_R = y\right] f_\tau(x)dx f_R(y)dy$$
$$= \int_0^\infty\int_0^\infty \frac{1}{x+y}\cdot f_\tau(x)dx\cdot f_R(y)dy$$
$$= \frac{1}{E[\tau(\lambda)]}\int_0^\infty\int_0^\infty \frac{\tau(x)}{x+y}\cdot f_\lambda(x)dx\cdot f_R(y)dy \quad (11)$$

where in the last equality we substituted the expression for f_τ from Proposition 1.

Finally, dividing Eq. (11) with Eq. (9) gives the expression of Result 1 for the delay ratio R. □

8.2.2 Source Delivery Probability, $P_{(src.)}$

Proof: Using similar arguments and notation as above, the event of the *message delivery by the source* is equivalent to the destination contacting the source before any other relay.

Then, $P_{(src.)} \equiv P\{T_{sd} < T_{r-d}\}$ (where $T_{r-d} = \min_{i\in\mathcal{L}}\{T_{id}\}$), will be given by the ratio $\frac{\lambda_{sd}}{\lambda_{sd}+X_R}$ [42]. Conditioning on the the rates λ_{sd} and X_R, we can write

$$P_{(src.)} \equiv P\{T_{sd} < T_{r-d}\} =$$
$$= \int_0^\infty\int_0^\infty P\{T_{sd} < T_{r-d}|\lambda_{sd} = x, X_R = y\} f_\tau(x)dx f_R(y)dy$$
$$= \int_0^\infty\int_0^\infty \frac{x}{x+y}\cdot f_\tau(x)dx\cdot f_R(y)dy$$

and substituting $f_\tau(x)$ from Proposition 1 gives

$$P_{(src.)} = \int_0^\infty\int_0^\infty \frac{x}{x+y}\cdot\frac{\tau(x)}{E[\tau(\lambda)]}\cdot f_\lambda(x)dx\cdot f_R(y)dy$$

which is equal to the expression for $P_{(src.)}$ in Result 1. □

8.3 Proof of Result 2

8.3.1 Delay Ratio, R

Proof: The expression for the delay ratio R of Result 1 can be written as

$$R = \frac{1}{E\left[\frac{\tau(\lambda)}{\lambda}\right]}\cdot\int_0^\infty E_R\left[\frac{1}{x+y}\right]\cdot\tau(x)\cdot f_\lambda(x)dx \quad (12)$$

where the expectation $E_R[\cdot]$ is taken over f_R. Using Jensen's inequality[17] for the function $h(y) = \frac{1}{x+y}$, we get:

$$E_R\left[\frac{1}{x+y}\right] \geq \frac{1}{x+E_R[y]} \quad (13)$$

where $E_R[y]$ is given by (as the expectation of a sum of L i.i.d. random variables with expectation μ_λ) [42]:

$$E_R[y] = E[X_R] = E\left[\sum_{i\in\mathcal{L}}\lambda_{id}\right] = L\cdot\mu_\lambda \quad (14)$$

Hence, using Eq. (13) and Eq. (14) in Eq. (12), we get

$$R \geq \frac{1}{E\left[\frac{\tau(\lambda)}{\lambda}\right]}\cdot\int_0^\infty \frac{\tau(x)}{x+L\cdot\mu_\lambda}\cdot f_\lambda(x)dx$$
$$= \frac{1}{E\left[\frac{\tau(\lambda)}{\lambda}\right]}\cdot E\left[\frac{\tau(\lambda)}{\lambda+L\cdot\mu_\lambda}\right] \quad (15)$$

Now, Eq. (15), for $\tau(x) = c\cdot x^k$, is written as

$$R \geq \frac{1}{E[\lambda^{k-1}]}\cdot E\left[\frac{\lambda^k}{\lambda+L\cdot\mu_\lambda}\right] \quad (16)$$

The expectations in Eq. (16) are taken over the contact rates'(*Gamma*) distribution, whose general form is [42]

$$f_\lambda(x) = \tfrac{\beta^\alpha}{\Gamma(\alpha)}x^{\alpha-1}e^{-\beta x}$$

where $\alpha > 0$ is the *shape* parameter, $\beta > 0$ the *rate* parameter. Its mean value and variance are given by $\mu_\lambda = \frac{\alpha}{\beta}$ and $\sigma_\lambda^2 = \frac{\alpha}{\beta^2}$, respectively, and, equivalently, we can write

$$\alpha = 1/CV_\lambda^2, \qquad \beta = 1/\left(\mu_\lambda\cdot CV_\lambda^2\right) \quad (17)$$

To calculate Eq. (16), first we find an expression for $E[\lambda^{k-1}]$:

$$E[\lambda^{k-1}] = \int_0^\infty x^{k-1}f_\lambda(x)dx = \int_0^\infty x^{k-1}\frac{\beta^\alpha}{\Gamma(\alpha)}x^{\alpha-1}e^{-\beta x}dx$$
$$= \frac{\Gamma(k-1+\alpha)}{\Gamma(\alpha)}\frac{1}{\beta^{k-1}}\int_0^\infty \frac{\beta^{k-1+\alpha}}{\Gamma(k-1+\alpha)}x^{(k-1+\alpha)-1}e^{-\beta x}dx$$
$$= \frac{\Gamma(k-1+\alpha)}{\Gamma(\alpha)}\frac{1}{\beta^{k-1}} \quad (18)$$

where the integral in the second line is equal to 1 because the integrated function is the pdf of a Gamma distribution with

17. Jensen's inequality for a convex function $h(x)$: $E[h(x)] \geq h\left(E[x]\right)$.

parameters $\alpha^{'} = k - 1 + \alpha$ (it must hold that $\alpha^{'} > 0$, which means that $k > 1 - \alpha = 1 - \frac{1}{CV_\lambda^2}$) and $\beta^{'} = \beta$.

Similarly to the derivation of Eq. (18), it can be shown that

$$\begin{aligned} E\left[\frac{\lambda^k}{\lambda + L\cdot\mu_\lambda}\right] &= \\ &= \frac{\Gamma(k+\alpha)}{\Gamma(\alpha)}\frac{1}{\beta^k}\cdot\int_0^\infty \frac{1}{x+L\cdot\mu_\lambda}\frac{\beta^{k+\alpha}}{\Gamma(k+\alpha)}x^{k+\alpha-1}e^{-\beta x}dx \\ &= \frac{\Gamma(k+\alpha)}{\Gamma(\alpha)}\frac{1}{\beta^k}\cdot E_{\lambda'}\left[\frac{1}{\lambda' + L\cdot\mu_\lambda}\right] \end{aligned} \tag{19}$$

where λ' follows a Gamma distribution with parameters $\alpha' = k + \alpha$ and $\beta' = \beta$. Since the function $g(x) = \frac{1}{x+c}$ is convex, we can apply Jensen's inequality to Eq. (19) and get

$$\begin{aligned} E\left[\frac{\lambda^k}{\lambda + L\cdot\mu_\lambda}\right] &\geq \frac{\Gamma(k+\alpha)}{\Gamma(\alpha)}\frac{1}{\beta^k}\cdot\frac{1}{E[\lambda'] + L\cdot\mu_\lambda} \\ &= \frac{\Gamma(k+\alpha)}{\Gamma(\alpha)}\frac{1}{\beta^k}\cdot\frac{1}{\frac{k+\alpha}{\beta} + L\cdot\mu_\lambda} \end{aligned} \tag{20}$$

where we substituted $E[\lambda'] = \frac{\alpha'}{\beta'} = \frac{k+\alpha}{\beta}$.

Thus, from Eq. (18) and Eq. (20), it holds for R (Eq. (16)):

$$R \geq \frac{\Gamma(k+\alpha)}{\Gamma(k-1+\alpha)}\cdot\frac{1}{\beta}\cdot\frac{1}{\frac{k+\alpha}{\beta}+L\cdot\mu_\lambda}$$

and because of the Gamma function's property $\Gamma(z+1) = z\cdot\Gamma(z)$, we can write

$$R \geq \frac{k-1+\alpha}{\beta}\cdot\frac{1}{\frac{k+\alpha}{\beta}+L\cdot\mu_\lambda} \tag{21}$$

and Eq. (2) follows easily by substituting α and β from Eq. (17) to Eq. (21). □

8.3.2 Source Delivery Probability, $P_{(src.)}$

Proof: Using the same notation, the expression for the delivery probability $P_{(src.)}$ of Result 1 can be written as

$$P_{(src.)} = \frac{1}{E[\tau(\lambda)]}\cdot\int_0^\infty E_R\left[\frac{x\cdot\tau(x)}{x+y}\right]\cdot f_\lambda(x)dx \tag{22}$$

and applying Jensen's inequality as in Eq. (13), we get

$$\begin{aligned} P_{(src.)} &\geq \int_0^\infty \frac{x\cdot\tau(x)}{x+L\cdot\mu_\lambda}\cdot f_\lambda(x)dx \\ &= \frac{1}{E[\tau(\lambda)]}\cdot E\left[\frac{\lambda\cdot\tau(\lambda)}{\lambda+L\cdot\mu_\lambda}\right] \end{aligned} \tag{23}$$

Now, setting $\tau(x) = c\cdot x^k$ in Eq. (23), gives

$$P_{(src.)} \geq \frac{1}{E[\lambda^k]}\cdot E\left[\frac{\lambda^{k+1}}{\lambda+L\cdot\mu_\lambda}\right] \tag{24}$$

Using Eq. (18) - Eq. (20) (where instead of k we consider $k+1$), the result for $P_{(src.)}$ follows similarly as before. □

8.4 Mobility Independent Heterogeneous Traffic

Heterogeneous communication traffic patterns that are independent of the underlying mobility, can be captured by the following definition (with respect to Def. 2).

Definition 4 (Mobility Independent Heterogeneous Traffic). *The end-to-end traffic demand (per time unit) between a pair of nodes $\{i,j\}$, is a random variable τ_{ij}, with finite mean value $E[\tau_{ij}] = \mu_\tau$, $\mu_\tau \in (0,\infty)$.*

Then, under Def. 4, Lemma 1 states that the effective contact rate between sources and destinations ($\lambda_{sd} \sim f_\tau(\lambda)$) is not different than the contact rate between a randomly chosen pair of nodes ($\lambda_{ij} \sim f_\lambda(\lambda)$). Therefore, it follows evidently that neither the *average* communication performance will be affected by traffic heterogeneity, when it is mobility independent.

Lemma 1. *The probability density function f_τ of the contact rate between the source and the destination $\{s,d\}$ of a random message, in a network following Definitions 1 and 4, converges in probability as follows:*

$$f_\tau(x) \xrightarrow{p} f_\lambda(x)$$

Proof: Let us consider the same notation and methodology as in the proof of Proposition 1. The key difference is that now (under Def. 4), the mean value of the random variables τ_{ij} is μ_τ (i.e. independent of mobility). Thus, it holds that for a large network (*weak law of large numbers*)

$$X_1 = \frac{T(\lambda)}{\|\mathcal{N}(\lambda)\|} \xrightarrow{p} \mu_\tau \quad \text{and} \quad X_3 = \frac{\sum_i\sum_i \tau_{ij}}{N(N-1)/2} \xrightarrow{p} \mu_\tau$$

Then, applying Cramér's theorem, gives

$$X_1\cdot X_2\cdot\frac{1}{X_3} \xrightarrow{p} \mu_\tau\cdot f_\lambda(\lambda)\cdot\frac{1}{\mu_\tau} = f_\lambda(\lambda)$$

which proves the Lemma. □

8.5 Mobility Aware Protocols - Proof of Corollary 1

Since the relay selection is mobility dependent, the contact rates between relays and destinations will *not* be distributed with f_λ. Following similar arguments as in the proof of Proposition 1 (Section 8.1), it can be shown that for mobility-aware protocols that follow the model presented in Section 5, Lemma 2 holds.

Lemma 2. *The contact rate between a relay and the destination of a random message, under mobility-aware routing, converges in probability as follows:*

$$f_u(x) \xrightarrow{p} \frac{1}{E[p(\lambda)]}\cdot p(x)\cdot f_\lambda(x) \tag{25}$$

where $E[p(\lambda)] = \int_0^\infty p(x)f_\lambda(x)dx$

Using Lemma 2, Results 1 and 2 are modified as following:

Result 1: The function f_R used in Result 1 (see also Eq. (10)-Eq. (11) in its proof) will be now the L-fold convolution of $f_u(\lambda)$ (rather than f_λ), i.e. $f_R = f_u^{(*L)}$.

Result 2: Since $f_R = f_u^{(*L)}$, the mean value $E_R[y]$ (see Eq. (14)) will be given now by

$$E_R[y] = L\cdot E_u[y] = L\cdot\int_0^\infty y\cdot f_u(y)dy \tag{26}$$

Substituting f_u from Eq. (25) to Eq. (26), gives

$$E_R[y] = L\cdot\int_0^\infty y\cdot\frac{p(y)}{E[p(\lambda)]}\cdot f_\lambda(y)dy = L\cdot\frac{E[\lambda\cdot p(\lambda)]}{E[p(\lambda)]} \tag{27}$$

where the expectations are taken over f_λ.

Comparing Eq. (14) and Eq. (26), it is easy to see that one need to replace the term $L \cdot \mu_\lambda$ with a term $L \cdot \frac{E[\lambda \cdot p(\lambda)]}{E[p(\lambda)]} = c_u \cdot L \cdot \mu_\lambda$, where

$$c_u = \frac{E[\lambda \cdot p(\lambda)]}{\mu_\lambda \cdot E[p(\lambda)]} = \frac{E[\lambda \cdot p(\lambda)]}{E[\lambda] \cdot E[p(\lambda)]} \tag{28}$$

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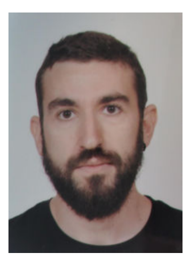

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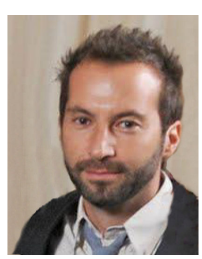

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